The impact of supply base complexity on disruptions and performance: The moderating effects of slack and visibility

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The impact of supply base complexity on disruptions and performance: The moderating effects of slack and visibility

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Abstract

In the face of increasing supply base complexity, organisations have to develop new ways to manage or mitigate risk. This paper investigates the impact of four dimensions of complexity on the frequency of disruptions and plant performance. We apply insights from Organisational Information Processing Theory to understand how organisations can mitigate against the impact of more frequent disruptions. We test the moderating effects of slack resources as a means to absorb the effects of disruptions and supply visibility as a means to improve the ability to handle disruptions. The model is tested with data from 264 supply chain management professionals. Our findings broadly support the original hypotheses and suggest that supply base complexity can increase the frequency of disruptions and reduce plant performance but that slack resources and visibility can help to mitigate the effects. The study offers valuable insights into the management of supply base complexity.

Keywords: supply base complexity, supply chain disruption, supply chain management, empirical study

1. Introduction

Supply base complexity refers to upstream complexity in the supply chain, which is created by large numbers of suppliers; suppliers which are different in terms of technical competence or size; long and/or unreliable lead-times; and the broad geographic dispersion of the supply base (Caridi *et al.* 2010). While complexity enables organisations to reach new markets and offer greater product variety (Isik 2009), it is generally perceived to have a negative effect on performance, or increase risk (Fridgen *et al.* 2014). Empirical evidence is generally supportive of the latter perspective where studies have found adverse consequences for supply chain vulnerability, plant performance, production and transaction costs, and supplier innovation (Choi and Krause 2006, Bozarth *et al.* 2009, Wagner and Neshat 2010).

Organisations negatively affected by supply base complexity have the choice of two broad options. The first option is to reduce complexity. For example, General Motors and General Electric rationalised the total number of suppliers in their supply base in order to reduce complexities and costs within their respective supply chains (Choi and Krause 2006). On the other hand, it is not always possible or even desirable to reduce complexity. The second option is therefore to accommodate complexity and find ways of limiting its effects. Organisational Information Processing Theory (OIPT) (Galbraith 1973, 1977) posits two mechanisms for accommodating the environmental uncertainty created by complexity: (1) strategies that reduce the amount of information processing required and therefore absorb the effects of uncertainty; and (2) strategies that increase information processing capacity and therefore enhance the organisation's ability to handle uncertainty. While prior research has successfully applied OIPT to the effects of manufacturing plant complexity (Flynn and Flynn 1999), this has yet to be extended to study complexity in the upstream supply base (cf. Bozarth *et al.* 2009).

Understanding the impacts of supply base complexity and how to reduce its negative effects are therefore timely and important questions for both research and practice. Building on prior research (Bozarth *et al.* 2009, Isik 2009), this study suggests that supply base complexity directly impacts the frequency of supply disruptions, which in turn impacts plant performance. Based on the principles of OIPT, we examine how the negative effects of disruptions can be mitigated through the development of slack resources and visibility within the supply base (Bode *et al.* 2011).

Our research seeks to make three main contributions to the empirical supply chain risk management literature (cf. Thun *et al.* 2011, Grötsch *et al.* 2013, Lavastre *et al.* 2014). First, we show that not all dimensions of supply base complexity have a negative effect on the frequency of disruptions. Specifically, our results indicate that the size of the supply base and lead-times that are long and/or unreliable have an impact on the frequency of disruptions but that geographic dispersion and the differentiation of suppliers do not have significant effects. Second, we answer calls for further empirical research in the area of supply chain risk management (Sodhi *et al.* 2012) to provide empirical evidence that the negative effects of disruptions can be reduced through the use of slack resources, in the form of capacity and inventory, and supply chain visibility. Third, we use insights from OIPT to show that slack resources and visibility are only of benefit to plant performance under conditions of frequent supply disruptions.

2. Theoretical background and hypothesis development

2.1 Supply Base Complexity

Supply base complexity relates to the upstream part of the focal firm's supply chain. Although supply base, or upstream, complexity is measured differently across studies (e.g. Bozarth et al., 2009; Choi and Krause, 2006), five components are commonly used in various combinations: the number of suppliers; the level of differentiation between suppliers; the delivery reliability and lead-time of suppliers; the geographic dispersion of suppliers; and the inter-relationships between suppliers (Vachon and Klassen 2002, Choi and Krause 2006, Caridi *et al.* 2010). The focus of this study is on the first four of these dimensions. While we acknowledge that inter-relationships between suppliers are an important component of complexity, they require data collection at the level of the supply network. Since this study relies on key informants located in the buyer plants, this fifth dimension could not be investigated.

The four dimensions we measure can be shown to contribute to complexity for a variety of reasons. First, the number of suppliers, or the scale of the supply base, necessarily increases complexity due to the greater number of information flows, physical flows and relationships to be managed (Bozarth *et al.* 2009). Second, differentiation among suppliers, in terms of size and technical ability, creates complexity as managers are forced to adapt to a range of cultures, practices and technical capabilities (Choi and Krause 2006). Third, unreliable and/or long supplier delivery creates complexity as managers must use more demand data (Frank *et al.* 2000), extend their planning horizons and engage in collaborative or supplier development activities (Simangunsong *et al.* 2012). Finally, the more geographically disparate suppliers are, the more complexity it creates through having to manage suppliers with different cultural or linguistic characteristics (Stringfellow *et al.* 2008), for example, as well as having the challenge of longer lead-times and variability in quality levels (Gray *et al.* 2011).

2.2 Organisational Information Processing Theory

Organisational Information Processing Theory (OIPT) centres on the notion that the greater the degree of task uncertainty, the greater the amount of information that needs to be processed by decision-makers during the task (Galbraith 1973). Organisations that face high uncertainty must gather, interpret and synthesise more information to successfully execute tasks than those in stable environments (Daft and Lengel 1986). Within this study, the task under consideration is the management of the upstream supply chain. Uncertainty is created as organisations must collect information on a greater number of variables in complex supply chains when compared to simple ones (Galbraith 1977). Sources of supply chain uncertainty, which are internal or upstream, may include: natural disasters, complexity, demand amplification; forecast horizons; the configuration and infrastructure of the supply chain; customer demand; and suppliers themselves (Simangunsong *et al.* 2012). Since supply base complexity increases uncertainty, further information is needed in order to manage it, therefore OIPT may be used as a theoretical perspective to understand how the supply chain may be more effectively managed under these conditions.

One method of managing uncertainty created by complexity is effective information processing. Information processing needs are defined as the communication requirements for inter-organisational interactions in the context of the supply chain (Premkumar *et al.* 2005). Given variability in information processing needs, organisations must develop an appropriate level of information processing capacity whereby the fit between needs and capacity will determine performance. To create fit, organisations can either: (1) develop buffers, such as multi-sourcing or additional capacity, that absorb uncertainty (and therefore the volume of information required); or (2) invest in mechanisms that improve organisations' capability to process more information (Galbraith 1973, Flynn and Flynn 1999). Supply chain managers will typically hold safety stock to buffer against the uncertainty created by the lag between demand and supply. Alternatively, they can share demand data through the supply chain in an effort to improve the process and quality of decision making (Mason-Jones and Towill

2000). These mechanisms may be utilised to reduce the uncertainty caused by supply base complexity and subsequently enable better management of complex supply chains.

We explicitly ground our hypothesis development in OIPT (cf. Gattiker 2007, Trentin *et al.* 2011). Specifically we explore the effects of the additional task complexity created by supply base complexity for the frequency of disruptions and their impact on performance. Our 'fit as moderation' model hypothesises that in general complexity increases the frequency of disruptions and in turn reduces performance, but that this may be offset by the creation of slack resources and/ or improving information processing capacity through visibility (cf. Galbraith, 1973). Figure 1 presents our hypothesised model.

[Figure 1 near here]

2.3 The effect of supply base complexity on the frequency of supply disruptions

Supply chain disruptions are defined as "unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain" (Craighead *et al.* 2007, p.132). Our study is concerned with the impact of supply base complexity on the frequency of disruption. Studies have previously found that supply base and supply chain complexity have a number of negative performance implications, including delivery speed and reliability (Vachon and Klassen 2002), responsiveness (Choi and Krause 2006), quality (Zhuo *et al.* 2009), overall plant performance (Bozarth *et al.* 2009) and the severity of disruptions (Craighead *et al.* 2007).

Because the four dimensions of complexity each represent a separate managerial decision, our study examines their effects independently. For example, managers could have a very large but domestic supply base and would thus be interested in the effects of scale but less in global dispersion. Alternatively, a manager might have a very homogeneous set of suppliers but very unreliable deliveries. Their interest would thus lie in the effect of delivery and less in the differentiation between suppliers. Based on these suppositions, we create a separate hypothesis for each of the four dimensions.

When a supply base has a large number of suppliers (high scale complexity), there is an increased likelihood of unreliable delivery (Choi and Krause, 2006). Although a very simple supply base, characterised by single-sourcing, might be of high risk due to reduced flexibility (Choi and Krause, 2006), it is deemed less likely to suffer from a higher frequency of disruptions than a more complex supply chain due to the number of actors involved in the network. Similarly, Smith *et al.* (1991) show that structural complexity reduces responsiveness as the transmission of information between organisations within the supply chain becomes modified, delayed or even completely blocked. Given that the movement of physical goods and services within the supply chain is driven by the flows of information, delay in the latter could very quickly lead to disruption of the former. Therefore,

H1a: The higher the scale complexity of a firm's supply base, the higher the frequency of supply disruptions

Firms with a high level of differentiation between their suppliers, in terms of technical capability or size, may experience coordination problems across their supply base (Choi and Krause, 2006). OIPT suggests that task complexity, here caused by the coordination problem stemming from differentiation, creates greater uncertainty and therefore greater information processing requirements. If these requirements are not met, organisational performance will suffer. Specifically, this may cause more frequent disruptions, such as late deliveries or inability to fulfil demand. Thus,

H1b: The higher the differentiation complexity of a firm's supply base, the higher the frequency of supply disruptions

An organisation which experiences delivery complexity, that is long lead-times and unreliability of delivery, may experience more frequent disruptions due to the greater distance to be travelled (Stecke and Kumar 2009), demand amplification effects such as the bullwhip (Lee *et al.* 1997) and less rapid responses to changes in end-customer demand (Simangunsong et al., 2012) thereby potentially experiencing more frequent disruptions than organisations with short lead-times. In addition, long lead time supply chains may also have less transparency enhancing the potential for disruptions. Subsequently,

H1c: The higher the delivery complexity of a firm's supply base, the higher the frequency of supply disruptions

With very geographically dispersed suppliers creating a truly global supply chain, the unpredictability of that supply chain increases in terms of delivery reliability (Manuj and Mentzer 2008) suggesting the potential for more frequent disruptions (Yang and Yang 2009). For example, Holweg *et al.* (2011) suggest that global supply chains are more likely to suffer from inventory obsolescence, stock-outs, greater expediting and increased stock holdings due to the risk of disruption to product flow. We hypothesise that:

H1d: The higher the geographic dispersion complexity of a firm's supply base, the higher the frequency of supply disruptions

2.4 The effect of supply disruptions on plant performance

Despite broad anecdotal evidence for the effect of disruptions on performance, empirical evidence remains limited. Studies have shown that supply chain disruptions may adversely affect operating performance, in terms of profitability, net sales, costs, and asset and inventory performance (Hendricks and Singhal 2005). Although Wagner and Bode (2008) find that supply chain risks affect performance in a negative manner, this is not consistent across all types of risk. This study examines the impact of the frequency of disruptions on plant performance, defined as a measure of the manufacturing plant's performance relative to competitors (Bozarth *et al.* 2009). The more frequently a disruption occurs within a given organisation, the more likely it is that plant performance will diminish as a result. This leads to hypothesis 2:

H2: The higher the frequency of supply disruptions, the lower the plant performance

2.5 The moderating effect of slack resources

Galbraith (1973) proposes two broad strategies for managing task uncertainty. The first of these is the creation of slack resources in order to reduce the need for information processing. Therefore, consistent with the reasoning of OIPT, we propose that an organisation can absorb the uncertainty created by complexity and supply disruptions through the creation of slack resources (Premkumar *et al.* 2005). There are a variety of slack resources available within the upstream supply chain, such as extra capacity and extra inventory (Chopra and Sodhi 2004), which are not directly related to one individual supplier (Bode et al., 2011). Although these approaches may reduce uncertainty, higher stock levels increase holding costs; and extra capacity requires initial investment and prevents working capital being deployed elsewhere. The creation of slack is therefore a decision to increase the resources available rather than utilise existing resources more efficiently (Galbraith 1973). Nevertheless, this does not mean that the use of slack resources is always the inferior, or more costly, choice. Investment decisions must be balanced against the alternative information processing choices, for example, holding extra inventory may be more cost efficient for a plant than investment in a customised ERP system.

Therefore, we suggest that slack resources moderate the relationship between frequency of disruptions and plant performance where slack is considered a core method for increasing supply chain resilience (Chopra and Sodhi 2004, Tang 2006) and has been shown to positively moderate the stock markets' reaction to disruptions (Hendricks *et al.* 2009). More specifically, we suggest that the introduction of extra capacity within the supply network and safety stock will help to offset the deleterious effects of disruptions on performance.

Extra capacity within the supply base may take the form of lower capacity utilisation at suppliers and the deliberate retention of back up suppliers even when the costs are higher (Sheffi and Rice Jr 2005). For example, Cisco Systems Inc. retains a capacity to manufacture higher value items in the US allowing for continuity of operations for the profitable home market in the face of a disruption (Chopra and Sodhi 2004). We suggest that extra capacity buffers organisations against disruptions where it can be used to divert products and manufacturing away from those parts of the supply base impacted by the disruption. More recently, Bode *et al.* (2011) also find that firms that experience large disruptions are more likely to add extra capacity and increase their independence from suppliers in subsequent time periods. This leads to the formulation of the following hypothesis:

H3a: Extra production capacity positively moderates the relationship between the frequency of supply chain disruptions and plant performance; the higher the level of production capacity, the lower the negative effects of disruption frequency on plant performance

Similarly, organisations may hold extra inventory as a means of creating slack to buffer against the effects of disruptions (Inman and Blumenfeld 2013). For example, to cope with a very complex supply chain (Brintrup *et al.* 2011) with many (potentially billions) of product variants, UK automotive manufacturers hold substantial stocks of finished goods inventory to buffer against uncertainty. This allows them to close the gap between customer choice and the lead-time of a build to order model thereby simultaneously improving delivery and flexibility performance†. Similarly, it has been reported that automakers, including Toyota, are starting to carry higher inventories of sensitive parts in the wake of the Japanese Tsunami disaster (Greimel 2012). These buffer stocks should allow operations to continue in the face of disruptions that may have previously ground to a halt within days due to lean and Just-in-Time operations. This leads to the formulation of the following hypotheses:

H3b: Safety stock at suppliers positively moderates the relationship between the frequency of supply chain disruptions and plant performance; the higher the level of safety stock at suppliers, the lower the negative effects of disruption frequency on plant performance

H3c: Safety stock at plant positively moderates the relationship between the frequency of supply chain disruptions and plant performance; the higher the level of safety stock at plant, the lower the negative effects of disruption frequency on plant performance

2.6 The moderating effect of supply chain visibility

According to Galbraith (1973), a second strategy for managing task uncertainty is to improve information processing capacity, for example through the creation of supply chain visibility. While slack resources reduce the amount of information that needs to be processed in any given task, an alternative strategy is to increase an organisation's information processing capacity to improve information collection, flow and accuracy (Tushman and Nadler 1978). Visibility, in terms of identifying and understanding inventory and demand levels across the upstream supply chain (Braunscheidel and Suresh 2009), improves an organisation's capability to process this information. Specifically, visibility allows members of the supply base to access useful information around the products' movement and, while enabled by technology, is not wholly dependent upon it (Caridi *et al.* 2010).

† Of course, finished goods inventory costs the manufacturers in the form of depreciation and sales incentives.

When supply chain visibility is enhanced, it has the potential to reduce the adverse effects of a supply chain disruption (Blackhurst *et al.* 2005) and also to improve supply chain resilience (Jüttner and Maklan 2011). The use of visibility systems may also allow earlier detection of disruptions (Sheffi & Rice, 2005). Greater visibility, created through improved knowledge and understanding of inventory and demand levels, allows organisations to proactively manage potential risks in their supply chain. Therefore:

H4: Visibility positively moderates the relationship between the frequency of supply chain disruptions and plant performance; the higher the visibility, the lower the negative effects of disruption frequency on plant performance

3. Methodology

3.1 Sample and procedure

A sample of 1200 United Kingdom manufacturing firms was surveyed from The Chartered Institute of Purchasing and Supply (CIPS) database. Respondents were selected by job function (supply chain manager or equivalent) and industry code (SIC 11000, 15000, 16000, 17000, 19000, 20000, 21000, 23000 – 36,000). In order to maximise response rate, respondents were first contacted by telephone to discuss the purpose of the survey, the commitment required and to invite participation. Second, a cover letter, survey and branded pen were sent to each respondent. The letter explained the purpose of the research and emphasised the endorsement from CIPS. We attempted to further maximise the response rate through a follow-up email after two weeks and a mailing after an additional four weeks. Respondents were also incentivised to participate through the offer of a donation to charity and a report of our findings.

We received 264 usable responses representing an effective response rate of 22.0%, meeting the threshold for effective operations management research (Malhotra and Grover 1998). A profile of respondents is provided in Table 1.

[Table 1 near here]

Non-response bias was tested through a comparison of early respondents (questionnaires received in the first two weeks), late respondents (questionnaires received in the third week or later) and non-respondents (a subsample of 25 non-respondents was selected at random from the initial contact list) (Armstrong and Overton 1977). Early and late respondents did not differ significantly on any of the variables used in this study while respondents and non-respondents did not differ significantly in terms of plant size or industry code suggesting that non-response bias is not likely to be a significant concern for our data sample.

3.2 Measures

Consistent with Bozarth *et al.* (2009), this study defined the unit of analysis as the upstream supply base of a manufacturing plant. Respondents were requested to answer all questions considering the inbound supply chain of their manufacturing plant. Likert scaled items were measured on a five-point scale.

Supply base complexity: A measure of upstream supply base complexity was developed from Bozarth *et al.* (2009), Choi and Krause (2006) and Caridi *et al.* (2010). Items reflected four dimensions of complexity: (a) scale, (b) differentiation, (c) delivery reliability, and (d) geographic dispersion. Upstream supply chains are considered more complex if they involve more actors, the actors are dissimilar, lead times are long and/or unreliable and actors more dispersed.

Scale was measured by the number of players, differentiation as the degree of difference in size and technical capability between suppliers (Caridi *et al.* 2010), and delivery reliability by on-time performance and lead time (Bozarth *et al.* 2009). Geographic dispersion was measured with an index developed by Stock *et al.* (2000). Respondents were asked to specify the percentage of their plant's suppliers located in the following regions: Europe, Asia, North America and Other. Dispersion was then calculated using the following formula:

$$\text{DISP} = 1 - \frac{(|\text{Europe}\% - 25| + |\text{Asia}\% - 25| + |\text{N. America}\% - 25| + |\text{Other}\% - 25|)}{150}$$

Values range from 0 where all suppliers are concentrated in a single region to 1 where all suppliers are spread equally across all four regions.

Frequency of Disruptions: Our analysis adopts the mean value of a six-item measure developed by Zsisidin and Wagner (2010) that examines the frequency with which a manufacturing plant has been disrupted due to suppliers.

Plant Performance: Our measure of plant performance consists of the four classic performance dimensions of cost, quality, flexibility and delivery (Rosenzweig and Roth 2004, Liu *et al.* 2012). We adopted the nine items developed in the High Performance Manufacturing (HPM) survey (Zhang *et al.* 2012) that includes the unit cost of manufacturing, inventory turnover, conformance to product specifications, product capability and performance, cycle time, on time delivery performance, fast delivery, flexibility to change product mix, and flexibility to change volume. The overall measure of plant performance is the mean of the four dimensions, an approach well embedded in the operations management literature (Naor *et al.* 2010).

Visibility: We measured visibility using a scale developed by Braunscheidel and Suresh (2009). The two items examined the extent to which inventory and demand levels are visible throughout the supply chain.

Slack resources: We measure three dimensions of slack resources that reflect the levels of extra production capacity in the network, safety stock at suppliers and safety stock at the plant (Sheffi and Rice Jr 2005).

Control variables:

We control for plant size and supplier concentration. Plant size has been previously linked to supply chain disruptions. For example Wagner and Neshat (2011) find that larger organisations are more vulnerable to supply chain relationships while Hendricks *et al.* (2009) find firm size is a significant control variable when analysing the abnormal returns from disruptions. We measure plant size by the log of the total number of employees at the plant.

Supplier concentration represents the number of suppliers accounting for 30% of the plant's purchasing budget (Vachon *et al.* 2009). Supplier concentration may impact the frequency of disruptions and plant performance where there may be less redundancy in the supply base.

3.3 Measure validation

To assess the quality of our measures in terms of their validity and reliability, we conducted confirmatory factor analysis (CFA). We conducted a CFA using MPlus 7 to estimate the measurement properties of the multi-item constructs. As shown in Table 2 all factor loadings were in excess of the commonly accepted 0.40 standard suggesting no need to delete items to improve model fit (Anderson and Gerbing 1988). The only exception was 'unit cost of manufacturing' that displays a marginal loading of 0.38, however, following Naor et al (2010), we retain the item for content validity purposes. The measurement model also revealed a good fit of the model to the data. We observed a chi-square value: X^2 (208) = 326.73; Tucker-Lewis Index (TLI) = .94; comparative fit index (CFI) = .95; and root mean square error of approximation (RMSEA) = .05, each supporting strong model fit.

[Table 2 near here]

To evaluate the psychometric properties of the measures, we analysed the validity and reliability of all the multi-item scales. Specifically, we assessed item reliability, convergent validity and discriminant validity (Fornell and Larcker 1981). The composite reliability of all constructs was above the threshold value of 0.70. Convergent validity was assessed on the basis of Cronbach's alpha and the significance of the factor loadings (t > 2.0) (Shah and Goldstein 2006). Discriminant validity of the constructs was assessed on the basis of the average variance extracted (AVE) for each measurement scale. The value for each construct should equal or exceed 0.50 (Fornell and Larcker 1981). As presented in Table 2, our scales exceed the recommended thresholds for each of the tests, indicating that the constructs have good reliability and convergent and discriminant validity. The only exception was the marginal Cronbach's Alpha ($\alpha = 0.68$) of delivery complexity, however, this is still within the limits of less established measures (Nunnally 1978).

3.4 Common Methods Bias

A major concern with self-reported survey data is common method variance, which is variance that is attributable to the measurement method rather than to the constructs the measures represent (Podsakoff *et al.* 2003). To test for common methods bias we conducted a modified version of Harman's one factor test as suggested by Malhotra *et al.* (2006). The fit indices indicated that a hypothesised model consisting of a single factor had very poor fit (X^2

(69) = 1619.156. TLI = .40; CFI = .34; RMSEA = .15). This suggests that common methods bias is not a concern for our data.

4. Results

Table 3 presents the correlations and descriptive statistics for each of the variables used in our study. Two dimensions of supply base complexity are positively correlated to the frequency of disruptions, which in turn, has a negative correlation with plant performance. The statistics also indicate relatively concentrated supply bases in our sample (mean = 0.19, SD = 0.19), a result which is broadly in line with prior studies (Lorentz *et al.* 2012).

[Table 3 near here]

The hypothesised relationships were tested using hierarchical moderated regression analysis. We mean-centred all model variables to reduce the risk of multicollinearity of the interaction terms (Aiken and West 1991). Additionally, we tested for collinearity by calculating the variance inflation factor for each of the regression coefficients in the model. Values ranged from 1.03 to 1.14, significantly below the cut-off value of 10 suggested by Hair *et al.* (1998).

Table 4 presents the results of the first regression analysis. Step 1 indicates that neither of the control variables had a significant effect on the frequency of disruptions. In step 2 we find that scale complexity ($\beta = .16$, $p < .01$) and delivery complexity ($\beta = .40$, $p < .01$) have significant effects. The results confirm hypotheses H1a and H1c and suggest that plants with a larger number of suppliers and longer and unreliable lead-times will be subject to more frequent supply disruptions. On the other hand, we find that differentiation and geographic dispersion do not have a significant effect on the frequency of disruptions.

[Table 4 near here]

Hypotheses two to four are tested in a regression model predicting plant performance. Results are displayed in Table 5. Step 1 shows that two of the control variables, scale complexity ($\beta = -0.18$, $p < .01$) and delivery complexity ($\beta = -.16$, $p < .01$), have significant negative effects on plant performance. These results are broadly in line with Bozarth et al (2009) who find negative, although not necessarily significant, effects of the number of suppliers and delivery performance for schedule attainment and the unit cost of manufacturing. Step 2 adds the frequency of disruptions to the regression model. The effect of the frequency of disruptions on plant performance is significant and negative ($\beta = -.18$, $p < .01$). The result confirms hypothesis 2, that plants with more frequent supply disruptions will have lower plant performance, but is also subject to interaction effects.

Step 3 adds the direct effects of the slack resources moderator terms. The results show extra production capacity has a significant direct positive effect on plant performance and that safety stock at the plant has a significant negative effect. Step 4 adds the interaction terms to our model. We find that both extra production capacity ($\beta = .11$, $p < .05$) and safety stock at suppliers ($\beta = .11$, $p < .05$) have a significant positive interaction with the frequency of disruptions. The results provide support for hypotheses 3a and 3b and indicate that the negative effects of disruption frequency may be reduced through these two types of slack. On the other hand, holding stock at the focal plant (hypothesis 3c) does not have a significant interaction effect.

The effect of visibility is tested in the same way. Step 5 adds the direct effect of visibility and step 6 adds the interaction term between the frequency of disruptions and visibility. We find that visibility has a significant positive direct effect ($\beta = .22$, $p < .01$) and a significant positive moderation effect ($\beta = .11$, $p < .05$). The results lend support for hypothesis 4 and show that the negative effects of disruption frequency may be reduced by increased supply chain visibility.

[Table 5 near here]

To further analyse the interaction effects, we estimate the simple slopes (Aiken and West 1991) of each of the significant interaction effects using values of one standard deviation above the mean to represent high levels of 'extra production capacity', 'safety stock at suppliers' and 'visibility' and one standard deviation below the mean to represent low values of these variables (Cohen and Cohen 1983). Figure 2a shows that in the situation of frequent supply disruptions, extra production capacity reduces the negative effects on plant performance. In order to clarify the meaning of the interaction effects we conduct a simple slope test, in which the slope is calculated by substituting the value of Z into the regression equation (Cohen and Cohen 1983, Dawson 2013). As demonstrated in Figure 2a, the impact of supply chain disruptions on plant performance is significant and negative for organisations with 'low' extra production capacity (-1 SD gradient = -1.83, $p < .001$), but non-significant for organisations with 'high' extra production capacity (+1 SD gradient = -.54, $p = .34$).

Figure 2b shows that in the situation of frequent supply disruptions, safety stock reduces the negative effects on plant performance. The simple slope test indicates the impact of supply chain disruptions on plant performance is significant and negative for organisations with 'low' safety stock at suppliers (-1 SD gradient = -1.90, $p < .001$) but non-significant for organisations with 'high' safety stock at suppliers (+1 SD gradient = -.46, $p = .51$). However, the figure also indicates a trade-off function where plant performance is lower for organisations with 'high' safety stock at suppliers when disruptions are infrequent. This finding may be explained due to the additional costs and deterioration of stock sitting at the supplier plant for indeterminate periods of time waiting for a disruption.

[Figures 2a and 2b near here]

Figure 3 shows that in the situation of frequent supply disruptions, visibility reduces the negative effects on plant performance. The simple slope test indicates the impact of supply chain disruptions on plant performance is significant and negative for organisations with ‘low’ visibility (+1 SD gradient = -3.09, $p < 0.01$) but non-significant for organisations with ‘high’ visibility (+1 SD gradient = -.50, $p = .39$).

[Figure 3 near here]

5. Discussion

Our study makes several contributions to the extant literature and theoretical understanding of issues relating to supply base complexity and performance. First, we find that the dimensions of supply base complexity have different effects on the frequency of disruptions. While prior research has been extremely valuable to our understanding of the link between complexity and risk (Craighead *et al.* 2007), our research adds further empirical precision to show that the number of suppliers and delivery complexities are the primary drivers of disruption frequency, while geographic dispersion and the differentiation between suppliers do not have a significant effect. Second, we add to the empirical base of supply chain risk management literature and follow calls from leading scholars in the field for further empirical work (Sodhi *et al.* 2012). Finally, we show that both slack resources and visibility have the potential to offset the negative effects of supply disruptions for plant performance. This complements previous research that indicates that slack and vertical relatedness may reduce the negative impact of disruptions on the stock market reaction (Hendricks *et al.* 2009). Our findings are discussed in more detail below.

5.1 Supply Complexity, Frequency of Disruptions, and Plant Performance

Complexity within global supply chains has been found to increase disruptions and reduce performance (Wagner and Bode 2006, Craighead *et al.* 2007, Bozarth *et al.* 2009). We find that supply base complexity in terms of scale (H1a) and delivery (H1c) leads to a decrease in performance due to an increase in the number of supply chain disruptions but that the effects of differentiation (H1b) and geographic dispersion (H1d) are found to be insignificant. We suggest that the scale of the supply base might lead to more frequent supply disruptions due to the increased nodes in the supply network and therefore an increased probability of disruptions at some point, and that the delivery complexity of the supply base might lead to more frequent disruptions because forecasting becomes more difficult for suppliers with long or unreliable lead-times.

However, an increase in the differentiation between suppliers does not affect the frequency of disruptions. Indeed if we consider the broad portfolio of spend in most manufacturing (Kraljic 1983), suppliers are likely to be differentiated based on the products and services supplied. Some will be basic commodities (non-critical items), while others will be the critical inputs into the process (strategic items). Purchasing professionals therefore become naturally accustomed to the variety within the supply base offsetting any issues for performance. We also find that the effect of geographic dispersion is non-significant. The two competing effects that are borne from global dispersion can perhaps explain this. On the one hand, organisations are exposed because of travel distances, time-zone differences, language differences, cultural distances (Stringfellow *et al.* 2008), and exchange rate fluctuations (Holweg *et al.* 2011). Such trends may increase risks. On the other hand, portfolio theory would suggest that a dispersed supply base actually reduces risks because the supply base is less dense (Craighead *et al.* 2007). These two competing pressures may help to explain our non-significant finding.

Despite broad anecdotal evidence for the effect of disruptions on performance, empirical evidence remains limited. We find that high frequency of supply chain disruptions decreases plant performance (H2). This may be explained by the consequences of disruptions that may affect different types of performance such as the quality of the finished product, flexibility and delivery, as well as cost.

5.2 Slack Resources and Visibility

OIPT posits a need to fit information processing capacity with information processing requirements. Disruptions are, by definition, unplanned and unanticipated events that limit an organisation's ability to operate in a pre-determined manner (cf. Craighead *et al.* 2007). Disruptions therefore increase an organisation's information processing requirements which can be met through the use of slack resources, such as extra production capacity, or safety stock at the plant or supplier, that act to reduce the need for information processing, or through the creation of greater visibility in the supply chain that improves an organisation's information processing capacity.

Previous studies suggest that the use of multiple suppliers, excess capacity and safety stock can be an effective means of creating resilience (Chopra and Sodhi 2004). However, such research was concerned with the direct effects of slack resources. We suggest that the use of extra production capacity, and supply stock at supplier (H3a and H3b) may moderate the relationship between the frequency of disruptions and plant performance. These slack resources effectively buffer against the uncertainty created by disruptions and subsequently reduce the negative impact on performance. Supply stock at the plant was not found to have this effect (H3c). Shortening product lifecycles and increasing product variety means that holding extra inventory in one's own plant may lead to excessive holding and obsolescence costs (Tang 2006) and therefore may negate the benefits of buffering against disruptions. Our study also confirms that visibility may reduce the effect of supply chain disruptions on plant performance (H4) as the information provided enables the focal organisation to quickly reallocate suppliers or products in the event of a disruption.

5.3 Managerial Implications

This study demonstrates the effect that different types of supply base complexity have on the frequency of supply disruptions. Since supply chain practitioners are especially interested in understanding supply chain disruptions (Craighead *et al.* 2007), and supply chains are becoming increasingly complex (Harland *et al*., 2003), it is important for managers to understand how complexity affects the frequency of disruptive events within the supply chain. Our study shows that complexity in terms of scale and delivery affects the frequency of disruptions whilst complexity in terms of differentiation and geographic dispersion does not. Therefore managers can concentrate on reducing the types of complexity that have the most impact.

Although more frequent disruptions lead to an adverse effect on plant performance, our findings suggest that there are ways to reduce this impact through the use of slack resources and visibility. By providing managers with an understanding of these strategies, they should be able to mitigate these negative consequences. Creating slack resources (extra production capacity and safety stock at supplier) can help to lessen the effect of supply chain disruptions on plant performance. An alternative approach is to improve visibility across the supply chain to enhance flexibility in the eventuality of a disruption.

5.4 Limitations and Future Research

The limitations of our study open both conceptual and methodological avenues for future research. First, studies could closely examine the balance between inventory, disruptions and costs. Our research provides empirical evidence for the trade-off between safety stock, disruptions and plant performance: higher performance is associated with low levels of supplier safety stock at low disruption frequency but high levels of supplier safety stock as disruptions become more frequent (Figure 2b). Future research could search for a balance between these variables to model the optimal stocking levels under varying frequency of disruptions to maximise performance considerations (including costs). Given that safety stock can also represent an inventory risk (Chopra and Sodhi 2004), models could also include different types of inventory, for example pooled inventory, to determine the effects of different inventory management strategies for varying individual performance variables, including costs and flexibility, as well as composite variables such as the one used in this study. Second, the same models could be applied to understand the optimal levels of capacity required. In particular, further research is required to understand the opportunity costs of capacity under-utilisation versus its benefits during a disruption.

Third, studies could examine the fit between the type of disruption and the methods used to offset the effect on performance. For example, is strategic stock preferable to visibility (and vice versa) for different causes of disruptions, for example operational contingencies, natural catastrophes or terrorism and political instability (Kleindorfer and Saad 2005)? Finally, in line with OIPT theorising, our study has examined the interaction effects of slack resources and visibility. Future studies could examine a broader portfolio of risk management techniques including flexible contracting, the availability of alternative sources of supply, postponement and network design (Tang 2006).

Table 1. Profile of Respondents.

Title	Number	Percentage
Annual Sales Revenue		
Under £10 Million	38	14.5
£11 – 25 Million	48	18.4
£26 – 50 Million	40	15.2
£51 – 75 Million	23	8.6
£76 – 100 Million	13	4.7
£101 – 250 Million	27	10.2
£251 – 500 Million	23	8.6
Over £501 Million	52	19.9
TOTAL	264	100
Number of employees		
0-50	31	11.7
51-100	45	17.2
101-200	50	18.8
201-500	62	23.4
501-1000	27	10.2
1001+	49	18.7
TOTAL	264	100
Industry Sector		
Oil and Gas	14	5.3
Food and Beverage	17	6.4
Textiles & Apparel	4	1.5
Wood products	1	0.4
Paper products	7	2.7
Chemical products	23	8.7
Rubber & plastic products	8	3
Basic & fabricated products	26	9.8
Machinery	48	18.2
Electrical and optical equipment	51	19.3
Automotive & transport	37	14
Furniture	26	9.8
TOTAL	264	100

Table 2. Factor Analysis.

Scales and associated indicators	Standardized factor loadings	Standard Error
Disruption occurence		
(Cronbach's α = .86; CR = .90; AVE = .61)		
Operations disrupted due to a late delivery from supplier	0.85	0.03
Operations disrupted due to a quality problem from supplier	0.76	0.03
Expedited shipments to avoid a disruption due to a late delivery	0.61	0.05
Late deliveries to customers	0.66	0.04
Unacceptable delivered quality from supplier	0.60	0.05
Excess costs (e.g. premium freight, higher prices from an alternate source) for this product due to a supplier's failure to perform	0.61	0.05
Plant performance		
(Cronbach's α = 83; CR = .81; AVE = .89)		
Unit cost of manufacturing	0.33	0.06
Inventory turnover	0.39	0.06
Conformance to product specifications	0.40	0.06
Product capability and performance	0.44	0.06
Cycle time (from raw materials to delivery)	0.69	0.04
On time delivery performance	0.80	0.03
Fast delivery	0.84	0.03
Flexibility to change product mix	0.67	0.04
Flexibility to change volume	0.66	0.04
Visibility		
(Cronbach's α = .81; CR = .94; AVE =.90)		
Inventory levels are visible throughout the supply chain	0.84	0.08
Demand levels are visible throughout the supply chain	0.78	0.07
Complexity Scale		
(Cronbach's α = .81; CR = .92; AVE =.87)		
This supply chain is very complex	0.99	0.09
This supply chain involves a lot of players (e.g. suppliers, logistics, service providers)	0.68	0.07
Differentiation Complexity		
(Cronbach's α = .73; CR = .95; AVE = .91)		
Suppliers in this supply chain are the same size	1.36	0.69
Suppliers in this supply chain have the same level of technical capability	0.43	0.22
Delivery Complexity		
(Cronbach's α = .68; CR = .93; AVE = .87)		
We can depend on on-time delivery from suppliers in this supply chain	0.90	0.06
We can depend on short lead times from suppliers in this supply chain	0.58	0.06

*CR and AVE require a model based test unavailable for two items constructs, factor loadings displayed are extrantion loadings based on Principal Component Analysis

** All constructs were scaled as 1 = strong disagree to 5 = strongly agree. The first tiem in each scale was fixed to a loading of 1.0 in the the initial run to set the scale of the construct. CFA Fit Statistics: X2 (208) = 326.73 ; TLI = .94; CFI = .95 ; RMSEA = .05.

Table 3. Descriptive Statistics and Intercorrelations of Constructs

No	Variable	M	SD	1	2	3	4	5	6	7	8	9	10
	Supply complexity												
1	Geographical dispersion	0.19	0.19	1									
2	Scale	3.64	0.91	.27**	1								
3	Differentiation	3.18***	0.78	.12	.12	1							
4	Delivery	2.03***	0.87	.03	.17**	-.05	1						
	Slack Resources												
5	Extra production capacity	2.71	0.87	.19**	.15*	.09	-.18**	1					
6	Safety stock at suppliers	2.74	0.99	.06	.08	.12	-.30**	.31**	1				
7	Safety stock at plant	2.89	0.96	.01	.11	-.03	.06	.14*	.25**	1			
8	Visibility	3.06	1.03	.14**	.05	-.07	-.23**	.22**	.21**	.03	1		
9	Frequency of Disruption	2.90	0.66	.07	.23**	.06	.43**	-.02	-.11	.02	-.14*	1	
10	Plant Performance	31.69	4.67	.01	-.21**	-.05	-.19**	.19**	0.08	-.09	.24**	-.25**	1

*Correlation is significant at the 0.05 level.
**Correlation is significant at the 0.01 level.
*** Scores are reversed.

Table 4. Regression Analysis for Frequency of Disruption

		Frequency of Disruption	
Step	Variables	1	2
1	**Control variables**		
	Plant size	.08	.02
	Supplier concentration	.09	.08
2	**Main effects**		
	Supply complexity		
	Geographical Dispersion		.00
	Scale		.16**
	Differentiation		.02
	Delivery		.40**
	R^2	.01	.22
	Adjusted R^2	.01	.20
	ΔR^2		.19**

* Significant at the 0.05 level
** Significant at the 0.01 level

Table 5. Regression Analysis for Plant Performance

Step	Variables	Plant Performance					
		1	2	3	4	5	6
1	**Control variables**						
	Plant size	-.09	-.09	-.11*	-.12*	-.09	-.09
	Supplier concentration	.04	.06	.05	.05	.05	.05
	Supply complexity						
	Geographical Dispersion	.08	.08	.05	.06	.05	.05
	Scale	-.18**	-.15**	-.17**	-.18**	-.17**	-.15**
	Differentiation	-.01	-.01	-.03	-.04	.01	.00
	Delivery	-.16**	-.09	-.02	-.02	-.04	-.03
2	**Main effect**						
	Frequency of Disruption (FoD)		-.18**	-.19**	-.17**	-.17**	-.17**
	Buffering effect						
3	Slack resources						
	Extra production capacity (EPC)			.22**	.21**		
	Safety stock at suppliers (SSAS)			.04	.03		
	Safety stock at plant (SSAP)			-.12**	-.13**		
4	Visibility (VIS)					.22**	.21**
	Interaction effect						
5	FoD x EPC				.11*		
	FoD x SSAS				.11*		
	FoD x SSAP				.05		
6	FoD x VIS						.11*
	R^2	.08	.10	.16	.19	.15	.16
	Adjusted R^2	.06	.08	.13	.15	.12	.13
	ΔR^2		.02*	.05**	.02*	.04*	.01*

* Significant at the 0.05 level
** Significant at the 0.01 level

Figure 1. Hypothesized model

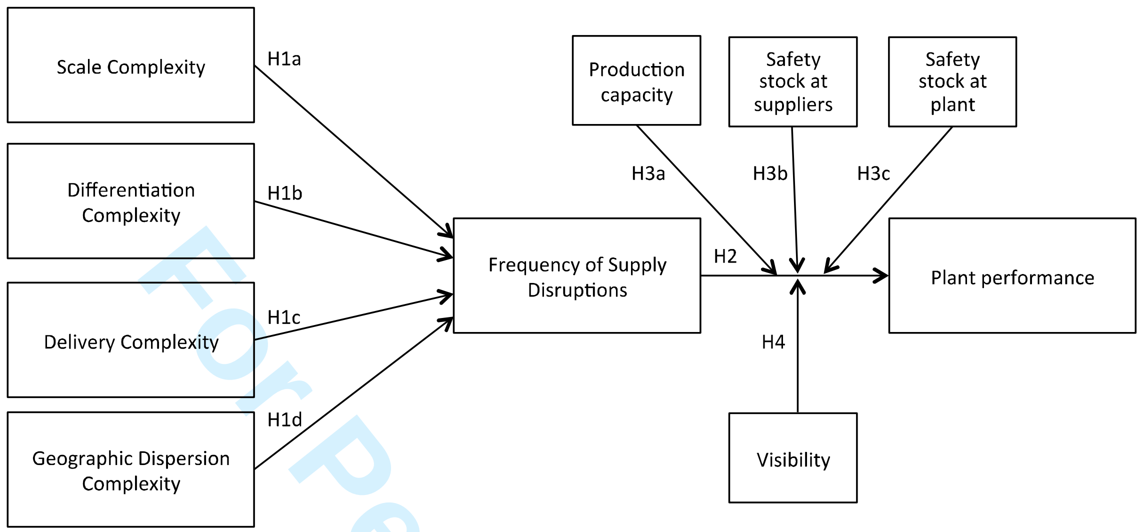


Figure 2. The interaction effects on plant performance (a) the moderation effect of extra production capacity, and (b) the moderation effect of safety stock at suppliers.

Figure 2a

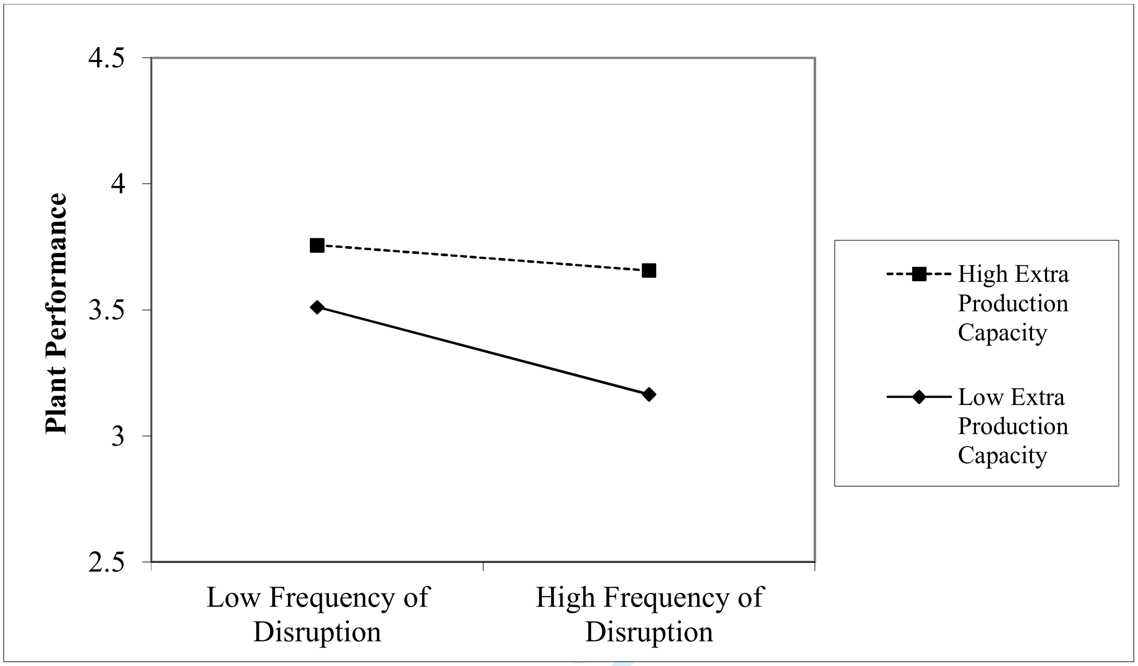


Figure 2b

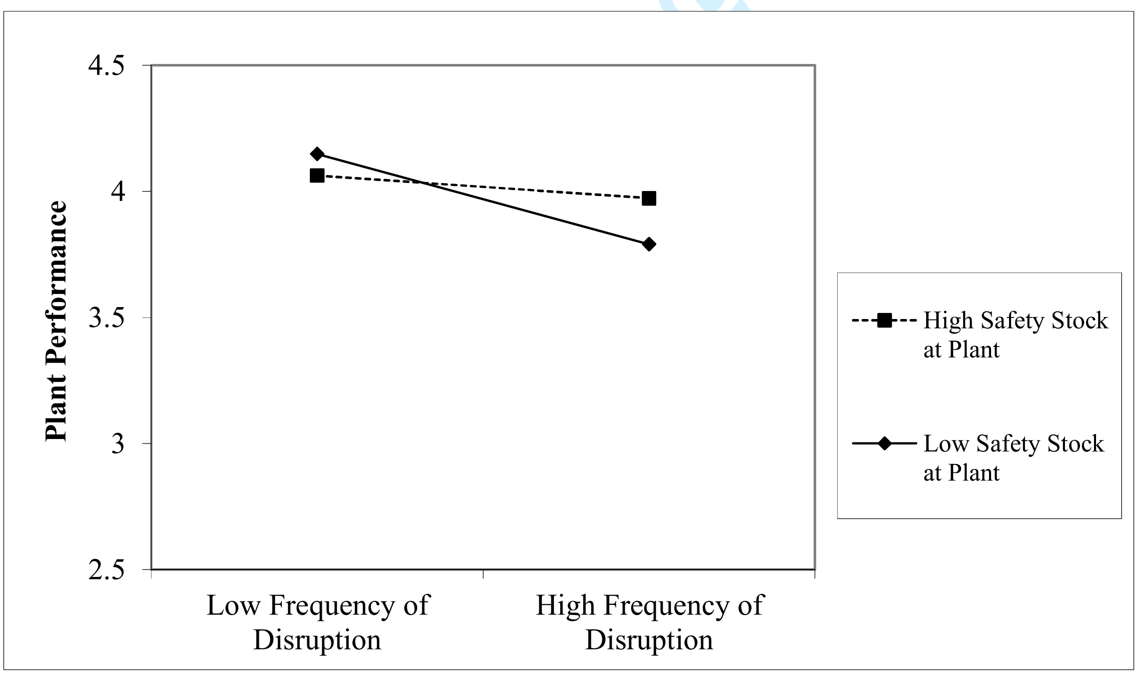
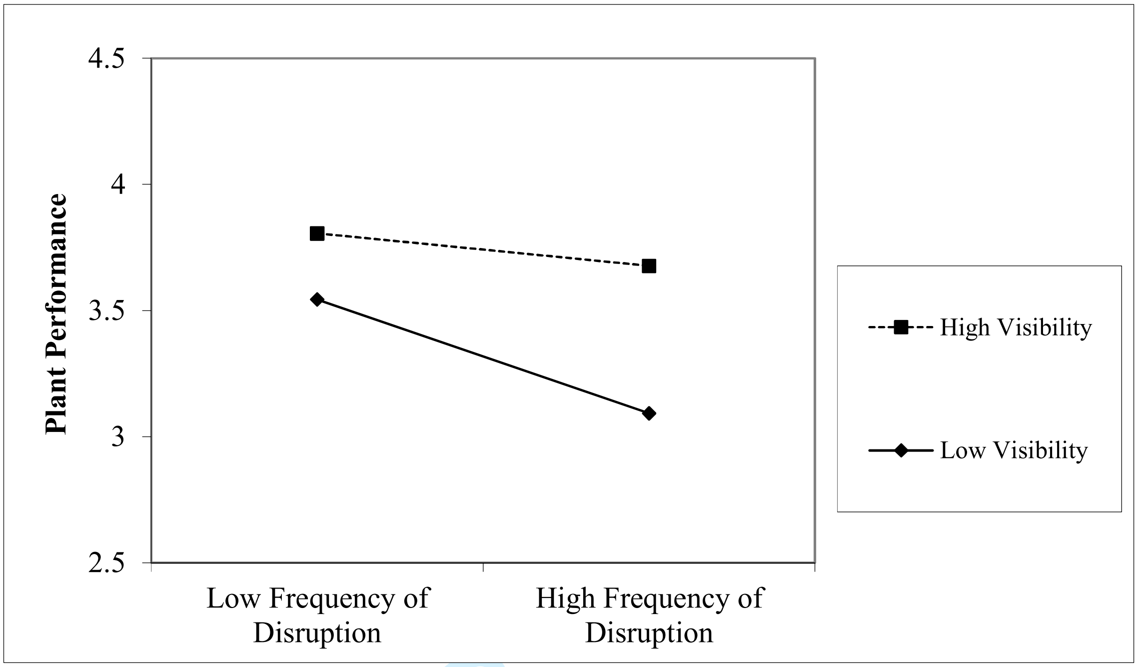


Figure 3. The interaction effect of visibility on plant performance.



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